

# $\Delta$ -ERGODIC THEORY AND RELIABILITY THEORY

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We show that the natural framework for the Markov chains considered in [5] is the  $\Delta$ -ergodic theory (in a more general context, the general  $\Delta$ -ergodic theory (see [8] and [11])) but not ergodic theory (for  $\Delta$ -ergodic theory see, e.g., [8], [9], [10], and [11] and for ergodic theory see, e.g., [2], [3], [4], and [12]). For this, we give in Section 1 the notions, notation, and results from  $\Delta$ -ergodic theory we need for the study of Markov chains from reliability theory. In Section 2 we then define and study these Markov chains.

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## 1. $\Delta$ -ERGODIC THEORY

In this section we deal with  $\Delta$ -ergodic theory which appears to be the natural framework for the study of Markov chains from [5].

Consider a finite Markov chain  $(X_n)_{n \geq 0}$  with state space  $S = \{1, 2, \dots, r\}$ , initial distribution  $\pi_0$ , and transition matrices  $(P_n)_{n \geq 1}$ . We frequently shall refer to it as the (finite) Markov chain  $(P_n)_{n \geq 1}$ . For all integers  $m \geq 0$ ,  $n > m$ , define

$$P_{m,n} = P_{m+1}P_{m+2} \cdots P_n = ((P_{m,n})_{ij})_{i,j \in S}.$$

(The entries of a matrix  $Z$  will be denoted  $Z_{ij}$ .)

Set

$$\text{Par}(E) = \{\Delta \mid \Delta \text{ is a partition of } E\},$$

where  $E$  is a nonempty set. We shall agree that the partitions do not contain the empty set, except for some cases (if needed) where this will be specified.

*Definition 1.1.* Let  $\Delta_1, \Delta_2 \in \text{Par}(E)$ . We say that  $\Delta_1$  is *finer than*  $\Delta_2$  if  $\forall V \in \Delta_1, \exists W \in \Delta_2$  such that  $V \subseteq W$ .

Write  $\Delta_1 \preceq \Delta_2$  when  $\Delta_1$  is finer than  $\Delta_2$ .

In  $\Delta$ -ergodic theory the natural space is  $S \times \mathbf{N}$ , called *state-time space*. Let  $\emptyset \neq A \subseteq S$  and  $\emptyset \neq B \subseteq \mathbf{N}$ . Let  $\Sigma \in \text{Par}(A)$ . Frequently, when we only use a partition  $\Sigma$  of  $A$  we shall omit to mention this. Also we can omit  $\Sigma$  if  $\Sigma = (\{i\})_{i \in A}$ .

*Definition 1.2* ([11]). Let  $i, j \in S$ . We say that  $i$  and  $j$  are in the same *weakly ergodic class on  $A \times B$*  (or *on  $A \times B$  with respect to  $\Sigma$* , or *on  $(A \times B, \Sigma)$*  when confusion can arise) if  $\forall K \in \Sigma, \forall m \in B$  we have

$$\lim_{n \rightarrow \infty} \sum_{k \in K} [(P_{m,n})_{ik} - (P_{m,n})_{jk}] = 0.$$

Write  $i \stackrel{A \times B}{\sim} j$  (with respect to  $\Sigma$ ) (or  $i \stackrel{(A \times B, \Sigma)}{\sim} j$ ) when  $i$  and  $j$  are in the same weakly ergodic class on  $A \times B$ . Then  $\stackrel{A \times B}{\sim}$  is an equivalence relation and determines a partition  $\Delta = \Delta(A \times B, \Sigma) = (C_1, C_2, \dots, C_s)$  of  $S$ . The sets  $C_1, C_2, \dots, C_s$  are called *weakly ergodic classes on  $A \times B$* .

*Definition 1.3* ([11]). Let  $\Delta = (C_1, C_2, \dots, C_s)$  be the partition of weakly ergodic classes on  $A \times B$  of a Markov chain. We say that the chain is *weakly  $\Delta$ -ergodic on  $A \times B$* . In particular, a weakly  $(S)$ -ergodic chain on  $A \times B$  is called *weakly ergodic on  $A \times B$*  for short.

*Definition 1.4* ([11]). Let  $(C_1, C_2, \dots, C_s)$  be the partition of weakly ergodic classes on  $A \times B$  of a Markov chain with state space  $S$  and  $\Delta \in \text{Par}(S)$ . We say that the chain is *weakly  $[\Delta]$ -ergodic on  $A \times B$*  if  $\Delta \preceq (C_1, C_2, \dots, C_s)$ .

In connection with the above notions and notation we mention some special cases ( $\Sigma \in \text{Par}(A)$ ):

1.  $A \times B = S \times \mathbf{N}$ . In this case we can write  $\sim$  instead of  $\stackrel{S \times \mathbf{N}}{\sim}$  (or  $\stackrel{\Sigma}{\sim}$  instead of  $\stackrel{(S \times \mathbf{N}, \Sigma)}{\sim}$ ) and can omit ‘on  $S \times \mathbf{N}$ ’ in Definitions 1.2, 1.3, and 1.4.
2.  $A = S$ . In this case we can write  $\stackrel{B}{\sim}$  instead of  $\stackrel{S \times B}{\sim}$  (or  $\stackrel{(B, \Sigma)}{\sim}$  instead of  $\stackrel{(S \times B, \Sigma)}{\sim}$ ) and can replace ‘ $S \times B$ ’ by ‘(time set)  $B$  (with respect to  $\Sigma$ )’ (or by ‘ $(B, \Sigma)$ ’) in Definitions 1.2, 1.3, and 1.4. A special subcase is  $B = \{m\} (m \geq 0)$ ; in this situation we can write  $\stackrel{m}{\sim}$  (or  $\stackrel{(m, \Sigma)}{\sim}$ ) and can replace ‘on (time set)  $\{m\}$ ’ by ‘at time  $m$ ’ in Definitions 1.2, 1.3, and 1.4.
3.  $B = \mathbf{N}$ . In this case we can set  $\stackrel{A}{\sim}$  instead of  $\stackrel{A \times \mathbf{N}}{\sim}$  (or  $\stackrel{(A, \Sigma)}{\sim}$  instead of  $\stackrel{(A \times \mathbf{N}, \Sigma)}{\sim}$ ) and can replace ‘ $A \times \mathbf{N}$ ’ by ‘(state set)  $A$  (with respect to  $\Sigma$ )’ (or by ‘ $(A, \Sigma)$ ’) in Definitions 1.2, 1.3, and 1.4.

*Definition 1.5* ([11]). Let  $C$  be a weakly ergodic class on  $A \times B$ . Let  $\emptyset \neq A_0 \subseteq A$  for which  $\exists K_1, K_2, \dots, K_p \in \Sigma$  such that  $A_0 = \bigcup_{u=1}^p K_u$ . Let  $\emptyset \neq B_0 \subseteq B$ . We say that  $C$  is a *strongly ergodic class on  $A_0 \times B_0$  with respect to  $A \times B$  (and  $\Sigma$ )* if  $\forall i \in C, \forall K \in \Sigma$  with  $K \subseteq A_0, \forall m \in B_0$  the limit

$$\lim_{n \rightarrow \infty} \sum_{j \in K} (P_{m,n})_{ij} := \sigma_{m,K} = \sigma_{m,K}(C)$$

exists and does not depend on  $i$ .

In connection with the last definition we mention some special cases:

1.  $A \times B = A_0 \times B_0$ . In this case we can say that  $C$  is a *strongly ergodic class on  $A \times B$* . A special subcase is  $A \times B = A_0 \times B_0 = S \times \mathbf{N}$  and  $C = S$  when we can say that the Markov chain itself is *strongly ergodic*.

2.  $A = A_0 = S$ . In this case we can say that  $C$  is a *strongly ergodic class on (time set)  $B_0$  with respect to (time set)  $B$* . If  $B = B_0$ , then we can say that  $C$  is a *strongly ergodic class on (time set)  $B$* . A special subcase of the case  $A = A_0 = S$  and  $B = B_0$  is  $B = B_0 = \{m\}$  when we can say that  $C$  is a *strongly ergodic class at time  $m$* .

3.  $B = B_0 = \mathbf{N}$ . In this case we can say that  $C$  is a *strongly ergodic class on (state set)  $A_0$  with respect to (state set)  $A$* . If  $A = A_0$ , then we can say that  $C$  is a *strongly ergodic class on (state set)  $A$* .

*Definition 1.6 ([11]).* Consider a weakly  $\Delta$ -ergodic chain on  $A \times B$  (with respect to  $\Sigma$ ). We say that the chain is *strongly  $\Delta$ -ergodic on  $A \times B$*  if any  $C \in \Delta$  is a strongly ergodic class on  $A \times B$ . In particular, a strongly ( $S$ )-ergodic chain on  $A \times B$  is called *strongly ergodic on  $A \times B$*  for short.

*Definition 1.7 ([11]).* Consider a weakly  $[\Delta]$ -ergodic chain on  $A \times B$ . We say that the chain is *strongly  $[\Delta]$ -ergodic on  $A \times B$*  if any  $C \in \Delta$  is included in a strongly ergodic class on  $A \times B$ .

Also, in these definitions we can simplify the language when referring to  $A$  and  $B$  (and  $\Sigma$ ). These are left to the reader.

Let

$$R_{m,n} = \{P \mid P \text{ is a real } m \times n \text{ matrix}\},$$

$$N_{m,n} = \{P \mid P \text{ is a nonnegative } m \times n \text{ matrix}\},$$

$$S_{m,n} = \{P \mid P \text{ is a stochastic } m \times n \text{ matrix}\},$$

and, for  $m = n := r$ ,

$$R_r = R_{r,r}, \quad N_r = N_{r,r}, \quad \text{and} \quad S_r = S_{r,r}.$$

Let  $T = (T_{ij}) \in R_{m,n}$ . Let  $\emptyset \neq U \subseteq \{1, 2, \dots, m\}$  and  $\emptyset \neq V \subseteq \{1, 2, \dots, n\}$ . Let  $\Delta \in \text{Par}(\{1, 2, \dots, m\})$ . Define

$$T_U = (T_{ij})_{i \in U, j \in \{1, 2, \dots, n\}}, \quad T^V = (T_{ij})_{i \in \{1, 2, \dots, m\}, j \in V}, \quad T_U^V = (T_{ij})_{i \in U, j \in V}$$

(in particular,  $T_{\{i\}}$ ,  $T^{\{j\}}$ , and  $T_{\{i\}}^{\{j\}}$  are the  $i$ th row of  $T$ , the  $j$ th column of  $T$ , and the entry  $T_{ij}$  of  $T$ , respectively; if  $Z \in R_{n,p}$ , then  $(TZ)_{ij} = (TZ)_{\{i\}}^{\{j\}} = T_{\{i\}} Z^{\{j\}}$ ),

$$\mu(T) = \max_{1 \leq j \leq n} \min_{1 \leq i \leq m} T_{ij}$$

(if  $T \in S_{m,n}$ , then  $\mu(T)$  is called *Markov's ergodicity coefficient of  $T$*  (see, e.g., [4, p. 56])),

$$\mu_{\Delta}(T) = \min_{K \in \Delta} \mu(T_K)$$

(see [7]),

$$\alpha(T) = \min_{1 \leq i, j \leq m} \sum_{k=1}^n \min(T_{ik}, T_{jk})$$

(if  $T \in S_{m,n}$ , then  $\alpha(T)$  is called *Dobrushin's ergodicity coefficient of  $T$*  (see, e.g., [2] or [4, p. 56])),

$$\bar{\alpha}(T) = \frac{1}{2} \max_{1 \leq i, j \leq m} \sum_{k=1}^n |T_{ik} - T_{jk}|,$$

$$\gamma_{\Delta}(T) = \min_{K \in \Delta} \alpha(T_K), \quad \bar{\gamma}_{\Delta}(T) = \max_{K \in \Delta} \bar{\alpha}(T_K)$$

(see [7] for  $\gamma_{\Delta}$  and  $\bar{\gamma}_{\Delta}$ ), and

$$|||T|||_{\infty} = \max_{1 \leq i \leq m} \sum_{j=1}^n |T_{ij}|$$

(the  $\infty$ -norm of  $T$ ).

If  $T \in S_{m,n}$  and  $\Delta \in \text{Par}(\{1, 2, \dots, m\})$ , then we have

$$\bar{\alpha}(T) = 1 - \alpha(T) \quad \text{and} \quad \bar{\gamma}_{\Delta}(T) = 1 - \gamma_{\Delta}(T)$$

(see [7]).

The following result shows that weak and strong ergodicity are kept back (good at a time, good in past) while weak and strong  $\Delta$ -ergodicity with  $\Delta \neq (S)$  are kept forward (bad at a time, bad in future).

**THEOREM 1.8.** *Let  $(P_n)_{n \geq 1}$  be a Markov chain. Let  $\Sigma = (\{i\})_{i \in S}$ .*

(i) *If the chain is weakly ergodic at time  $m_0$  ( $m_0 \geq 0$ ), then it is weakly ergodic at any time  $m \leq m_0$  ( $m \geq 0$ ).*

(ii) *If the chain is weakly  $\Delta$ -ergodic at time  $m_0$  with  $\Delta \neq (S)$ , then  $\forall m \geq m_0$ ,  $\exists \Delta_m \in \text{Par}(S)$  with  $\Delta_m \neq (S)$  such that it is weakly  $\Delta_m$ -ergodic at time  $m$ .*

(iii) *If the chain is strongly ergodic at time  $m_0$ , then it is strongly ergodic at any time  $m \leq m_0$ .*

(iv) *If the chain is strongly  $\Delta'$ -ergodic ( $A \times B = S \times \mathbf{N}$ ) and strongly  $\Delta$ -ergodic at time  $m_0$  with  $\Delta \neq (S)$ , then  $\forall m \geq m_0$ ,  $\exists \Delta_m \in \text{Par}(S)$  with  $\Delta_m \neq (S)$  such that it is strongly  $\Delta_m$ -ergodic at time  $m$ .*

*Proof.* (i) See, e.g., [4, p. 218].

(ii) See [3, p. 242] (where different notions and notation are used) or the argument below. Suppose that  $\exists m_1 > m_0$  such that the chain is weakly

ergodic ( $\Delta_{m_1} = (S)$ ) at time  $m_1$ . By (i), the chain is weakly ergodic at any time  $m \leq m_1$ , and we reached a contradiction.

(iii) Let  $\Pi_{m_0} = \lim_{n \rightarrow \infty} P_{m_0, n}$  ( $\Pi_{m_0}$  is a stable stochastic matrix, i.e., a stochastic matrix with identical rows).

*Case 1.*  $m_0 = 0$ . Obvious.

*Case 2.*  $m_0 > 0$ . Let  $0 \leq m < m_0$ . Then

$$P_{m, n} = P_{m, m_0} P_{m_0, n} \rightarrow P_{m, m_0} \Pi_{m_0} = \Pi_{m_0} \text{ as } n \rightarrow \infty,$$

i.e., the chain is strongly ergodic at time  $m$  (with the same limit matrix  $\Pi_{m_0}$ ).

(iv) If the chain is strongly  $\Delta'$ -ergodic, then  $\forall m \geq 0, \exists \Delta_m \in \text{Par}(S)$  such that it is strongly  $\Delta_m$ -ergodic at time  $m$ . Let us show that  $\Delta_m \neq (S)$ ,  $\forall m > m_0$ . Suppose that  $\exists m_1 > m_0$  such that the chain is strongly ergodic at time  $m_1$ . By (iii), the chain is strongly ergodic at any time  $m \leq m_1$ , and we reached a contradiction.  $\square$

*Definition 1.9 ([9]).* Let  $(P_n)_{n \geq 1}$  and  $(P'_n)_{n \geq 1}$  be two (finite) Markov chains. We say that  $(P'_n)_{n \geq 1}$  is a *perturbation of the first type* of  $(P_n)_{n \geq 1}$  if

$$\sum_{n \geq 1} \|P_n - P'_n\|_\infty < \infty.$$

**THEOREM 1.10.** Let  $(P_n)_{n \geq 1}$  be a Markov chain and  $(P'_n)_{n \geq 1}$  a perturbation of the first type of it. Let  $\Sigma = (\{i\})_{i \in S}$  ( $\Sigma \in \text{Par}(S)$ ).

- (i)  $(P_n)_{n \geq 1}$  is weakly ergodic if and only if  $(P'_n)_{n \geq 1}$  is weakly ergodic.
- (ii)  $(P_n)_{n \geq 1}$  is weakly  $\Delta$ -ergodic with  $\Delta \neq (S)$  if and only if  $(P'_n)_{n \geq 1}$  is weakly  $\Delta'$ -ergodic with  $\Delta' \neq (S)$ .
- (iii)  $(P_n)_{n \geq 1}$  is strongly ergodic if and only if  $(P'_n)_{n \geq 1}$  is strongly ergodic.
- (iv)  $(P_n)_{n \geq 1}$  is strongly  $\Delta$ -ergodic with  $\Delta \neq (S)$  if and only if  $(P'_n)_{n \geq 1}$  is strongly  $\Delta'$ -ergodic with  $\Delta' \neq (S)$ .

*Proof.* (i) See Theorem 1.33 in [9].

(ii) This follows from (i).

(iii) See Theorem 1.47 in [9].

(iv) This follows from (iii). It also follows from Theorem 6 in [3] (where different notions and notation are used).  $\square$

**THEOREM 1.11.** Let  $P \in S_r$  with a single closed set  $R$  (see, e.g., [4, p. 81] ( $\emptyset \neq R \subseteq \{1, 2, \dots, r\}$ )). Suppose that  $R$  is aperiodic and  $\exists i \in R$  such that  $P_{ii} > 0$ . Then

- (i)  $(P^{r-1})_{\{i\}} > 0$ ;
- (ii)  $\mu(P^{r-1}) > 0$  and  $\alpha(P^{r-1}) > 0$ .

*Proof.* (i) Let  $j \in \{1, 2, \dots, r\}$ . By hypothesis,  $\exists i_1, i_2, \dots, i_p \in \{1, 2, \dots, r\}$  for which  $i_k \neq i_l, \forall k, l \in \{1, 2, \dots, p\}$  with  $k \neq l$  such that  $j = i_1, i = i_p$ , and

$P_{i_s i_{s+1}} > 0, \forall s \in \{1, 2, \dots, p-1\}$ . Obviously,  $1 \leq p \leq r$ . Now,

$$(P^{r-1})_{ji} \geq P_{i_1 i_2} P_{i_2 i_3} \cdots P_{i_{p-1} i_p} P_{i_p i_p} \cdots P_{i_p i_p} > 0.$$

Therefore,  $(P^{r-1})^{\{i\}} > 0$ .

(ii) By (i),  $\mu(P^{r-1}) > 0$ . By  $\mu \leq \alpha$  and  $\mu(P^{r-1}) > 0$ , we have  $\alpha(P^{r-1}) > 0$ .  $\square$

Define

$$\mathcal{R}_{m,n}^{ij} = \{P \mid P \in S_{m,n} \text{ and } P_{ij} = 1\},$$

where  $i \in \{1, 2, \dots, m\}$  and  $j \in \{1, 2, \dots, n\}$ . In particular, if  $i = j := k$  and  $m = n := r$ , set

$$\mathcal{R}_r^k = \mathcal{R}_{r,r}^{kk} \quad (\mathcal{R}_r^k = \{P \mid P \in S_r \text{ and } P_{kk} = 1\}).$$

**THEOREM 1.12.** *The following statements hold.*

- (i) *If  $P \in \mathcal{R}_{m,n}^{ij}$  and  $Q \in \mathcal{R}_{n,p}^{jk}$  ( $i \in \{1, 2, \dots, m\}$ ,  $j \in \{1, 2, \dots, n\}$ ,  $k \in \{1, 2, \dots, p\}$ ), then  $PQ \in \mathcal{R}_{m,p}^{ik}$ .*
- (ii)  *$\forall i \in S_r$ ,  $\mathcal{R}_r^i$  is closed under multiplication.*

*Proof.* (i) We have

$$(PQ)_{ik} = P_{\{i\}} Q^{\{k\}} = P_{ij} Q_{jk} = 1,$$

i.e.,  $PQ \in \mathcal{R}_{m,p}^{ik}$ .

(ii) This follows from (i).  $\square$

**THEOREM 1.13.** *Let  $P \in \mathcal{R}_{m,n}^{ij}$ . Then*

$$\alpha(P) = \mu(P) = \mu(P^{\{j\}}).$$

*Proof.* We know that  $\mu(P) \leq \alpha(P)$  since  $\mu \leq \alpha$ . Further, let us show that  $\mu(P) \geq \alpha(P)$ . From  $P \in S_{m,n}$  and  $P_{ij} = 1$  we have  $P_{ik} = 0, \forall k \in \{1, 2, \dots, n\}, k \neq j$ . It follows that

$$\mu(P) = \min_{1 \leq l \leq m} P_{lj}.$$

Let  $u \in \{1, 2, \dots, m\}$  such that  $\mu(P) = P_{uj}$ . Further,

$$\sum_{k=1}^n \min(P_{uk}, P_{ik}) = \min(P_{uj}, P_{ij}) = P_{uj} = \mu(P).$$

Therefore,

$$\alpha(P) \leq \mu(P).$$

By  $\mu(P) \leq \alpha(P)$  and  $\mu(P) \geq \alpha(P)$ , we have

$$\alpha(P) = \mu(P).$$

Now,

$$\mu(P) = \min_{1 \leq l \leq m} P_{lj} = \mu(P^{\{j\}}).$$

Therefore,

$$\mu(P) = \mu(P^{\{j\}}). \quad \square$$

More generally, we have the following result.

**THEOREM 1.14.** *Let  $P \in S_{m,n}$  and  $\Delta \in \text{Par}(\{1, 2, \dots, m\})$ . Suppose that  $\forall K \in \Delta, \exists i = i(K) \in K, \exists j = j(K) \in \{1, 2, \dots, n\}$  such that  $P_K \in \mathcal{R}_{|K|,n}^{lj}$ , where  $l$  ( $l \in \{1, 2, \dots, |K|\}$ ) is the row of  $P_K$  ( $P_K \in S_{|K|,n}$ ) corresponding to  $i$  ( $(P_K)_{lj} = P_{ij} = 1$ ). Then*

$$\gamma_\Delta(P) = \mu_\Delta(P) = \min_{K \in \Delta, u=u(K)} \mu(P_K^{\{u\}}),$$

where  $u = u(K) \in U_K := \{w \mid w \in \{1, 2, \dots, n\} \text{ and } \exists v \in K \text{ such that } P_{vw} = 1\}$  is given,  $\forall K \in \Delta$ .

*Proof.* By Theorem 1.13, we have

$$\gamma_\Delta(P) = \min_{K \in \Delta} \alpha(P_K) = \min_{K \in \Delta} \mu(P_K) = \mu_\Delta(P).$$

The second equality follows from Theorem 1.13 and  $\mu_\Delta(P) = \min_{K \in \Delta} \mu(P_K)$ .  $\square$

A vector  $x \in \mathbf{R}^n$  will be understood as a row vector and  $x'$  is its transpose.

Consider also the canonical basis  $(e_i(n))_{i \in \{1, 2, \dots, n\}}$  of  $\mathbf{R}^n$  and  $e(n) = \sum_{i=1}^n e_i(n)$  (i.e.,  $e(n) = (1, 1, \dots, 1)$ ).

**THEOREM 1.15.** *Let  $(P_n)_{n \geq 1}$  be a Markov chain.*

(i) *If  $P_n \in \mathcal{R}_r^i$  ( $i \in S = \{1, 2, \dots, r\}$ ),  $\forall n \geq 1$ , then  $\exists \Delta \in \text{Par}(S)$  such that the chain is strongly  $\Delta$ -ergodic on  $\{i\}$  ( $A = \{i\}$ ,  $B = \mathbf{N}$ ,  $\Sigma = (\{i\}) \in \text{Par}(\{i\})$ ).*

(ii) *(a generalization of (i)) Let*

$$G = \{i \mid i \in S \text{ and } P_n \in \mathcal{R}_r^i, \forall n \geq 1\}.$$

*If  $G \neq \emptyset$ , then  $\exists \Delta \in \text{Par}(S)$  such that the chain is strongly  $\Delta$ -ergodic on  $G$  ( $A = G$ ,  $B = \mathbf{N}$ ,  $\Sigma = (\{i\})_{i \in G} \in \text{Par}(G)$ ).*

(iii) *(another generalization of (i)) If  $\exists H, \emptyset \neq H \subseteq S$ , such that  $(P_n)_H^H = Q_n$ ,  $\forall n \geq 1$ , where  $Q_n \in S_{|H|}$ ,  $\forall n \geq 1$ , then  $\exists \Delta \in \text{Par}(S)$  such that the chain is strongly  $\Delta$ -ergodic on  $H$  with respect to  $(H)$  ( $\Sigma = (H) \in \text{Par}(H)$ ).*

*Proof.* (i) This follows from (iii).

(ii) Obviously,  $\exists \Delta \in \text{Par}(S)$  such that the chain  $(P_n)_{n \geq 1}$  is strongly  $\Delta$ -ergodic on  $G$  if and only if  $\forall i \in G, \exists \Delta' = \Delta'(i)$  such that it is strongly  $\Delta'$ -ergodic on  $\{i\}$ . Now, (ii) follows from (i).

(iii) Let  $i \in S$ . We have

$$\begin{aligned} (P_{m,n+1})_{\{i\}}^H &= (P_{m,n})_{\{i\}} (P_{n+1})^H \geq (P_{m,n})_{\{i\}}^H (P_{n+1})_H^H = \\ &= (P_{m,n})_{\{i\}}^H Q_{n+1}, \quad \forall m, n, \quad 0 \leq m < n. \end{aligned}$$

Set  $t = |H|$ . Further,

$$(P_{m,n+1})_{\{i\}}^H e'(t) \geq (P_{m,n})_{\{i\}}^H Q_{n+1} e'(t) = (P_{m,n})_{\{i\}}^H e'(t), \quad \forall m, n, \quad 0 \leq m < n.$$

Therefore,  $((P_{m,n})_{\{i\}}^H e'(t))_{n \geq m}$  is an increasing sequence,  $\forall m \geq 0$ . This implies that  $((P_{m,n})_{\{i\}}^H e'(t))_{n \geq m}$  is convergent,  $\forall m \geq 0$ . Consequently,  $\exists \Delta \in \text{Par}(S)$  such that the chain  $(P_n)_{n \geq 1}$  is strongly  $\Delta$ -ergodic on  $H$  with respect to  $(H)$ .  $\square$

**THEOREM 1.16.** *Let  $(P_n)_{n \geq 1}$  be a Markov chain.*

(i) *If  $\exists \Delta \in \text{Par}(S)$  such that the chain is strongly  $\Delta$ -ergodic on  $A \times B$  with respect to  $\Sigma$ , then  $\exists \Delta' \in \text{Par}(S)$  with  $\Delta \preceq \Delta'$  such that it is strongly  $\Delta'$ -ergodic on  $\mathcal{C}A \times B$  with respect to  $(\mathcal{C}A)$ , where  $\mathcal{C}A$  is the complement of  $A$ .*

(ii) *The chain is strongly  $\Delta$ -ergodic on  $A \times B$  with respect to  $(A)$  if and only if it is strongly  $\Delta$ -ergodic on  $\mathcal{C}A \times B$  with respect to  $(\mathcal{C}A)$ . In particular, the chain is strongly ergodic on  $A$  with respect to  $(A)$  if and only if it is strongly ergodic on  $\mathcal{C}A$  with respect to  $(\mathcal{C}A)$ .*

*Proof.* Obvious.  $\square$

The following two results show that  $\Delta$ -ergodic theory can be used to obtain results in ergodic theory (for other examples see, e.g., Theorems 3.6, 3.10, and 3.12 in [10] (the latter is Theorem 1.23 below)).

**THEOREM 1.17.** *Let  $(P_n)_{n \geq 1}$  be a Markov chain. Let  $\Sigma = (\{i\})_{i \in S}$ ,  $\emptyset \neq K \subseteq S$ ,  $w \in S$ , and  $s \geq 0$ . Suppose that  $\exists t > s$ ,  $\exists u = u(t) \in K$  such that  $(P_{s,t})_{\{u\}} > 0$ . Then the following statements are equivalent.*

(i) *The chain is strongly ergodic at any time  $m$ ,  $0 \leq m \leq t$ , with*

$$\lim_{n \rightarrow \infty} P_{m,n} = e'(r)e_w(r) := \Pi, \quad \forall m, \quad 0 \leq m \leq t.$$

(Obviously,  $\Pi^{\{w\}} = e'(r)$ .)

(ii)  *$K$  is included in a strongly ergodic class at time  $s$  with*

$$\lim_{n \rightarrow \infty} (P_{s,n})_K = e'(v)e_w(r),$$

where  $v := |K|$ .

*Proof.* (i) $\Rightarrow$ (ii) Obvious.



(ii) $\Rightarrow$ (i) Let  $0 \leq m < t$  and  $n > t$ . We have

$$(P_{s,n})_{\{u\}}^{\mathcal{C}\{w\}} = (P_{s,t}P_{t,n})_{\{u\}}^{\mathcal{C}\{w\}} = (P_{s,t})_{\{u\}} (P_{t,n})^{\mathcal{C}\{w\}}.$$

Because  $\lim_{n \rightarrow \infty} (P_{s,n})_{\{u\}}^{\mathcal{C}\{w\}} = 0$  (the zero vector) and  $(P_{s,t})_{\{u\}} > 0$ , we have

$$\lim_{n \rightarrow \infty} (P_{t,n})^{\mathcal{C}\{w\}} = 0 \text{ (the zero matrix).}$$

Therefore,

$$\lim_{n \rightarrow \infty} P_{t,n} = \Pi.$$

Hence the chain is strongly ergodic at time  $t$ . Further,

$$P_{m,n} = P_{m,t}P_{t,n} \rightarrow P_{m,t}\Pi = \Pi \text{ as } n \rightarrow \infty,$$

i.e., the chain is strongly ergodic at time  $m$  with  $\lim_{n \rightarrow \infty} P_{m,n} = \Pi$ .  $\square$

**THEOREM 1.18.** *Let  $(P_n)_{n \geq 1}$  be a Markov chain. Let  $\Sigma = (\{i\})_{i \in S}$ ,  $\emptyset \neq K \subseteq S$ ,  $w \in S$ , and  $s \geq 0$ . Suppose that there exist two sequences  $s < t_1 < t_2 < \dots$  and  $u_1 = u_1(t_1) \in K$ ,  $u_2 = u_2(t_2) \in K, \dots$  such that  $(P_{s,t_l})_{\{u_l\}} > 0$ ,  $\forall l \geq 1$ . Then the following statements are equivalent.*

(i) *The chain is strongly ergodic with*

$$\lim_{n \rightarrow \infty} P_{m,n} = e'(r)e_w(r) := \Pi, \quad \forall m \geq 0.$$

(ii)  *$K$  is included in a strongly ergodic class at time  $s$  with*

$$\lim_{n \rightarrow \infty} (P_{s,n})_K = e'(v)e_w(r),$$

where  $v := |K|$ .

*Proof.* (i) $\Rightarrow$ (ii) Obvious.

(ii) $\Rightarrow$ (i) As in the proof of (ii) $\Rightarrow$ (i) in Theorem 1.17, the chain is strongly ergodic at time  $t_l$  with  $\lim_{n \rightarrow \infty} P_{t_l,n} = \Pi$ ,  $\forall l \geq 1$ . Now, let  $m \geq 0$ . Obviously,  $\exists l \geq 1$  such that  $m < t_l$ . Further, for  $n > t_l$ ,

$$P_{m,n} = P_{m,t_l}P_{t_l,n} \rightarrow P_{m,t_l}\Pi = \Pi \text{ as } n \rightarrow \infty,$$

i.e., the chain is strongly ergodic at time  $m$  with  $\lim_{n \rightarrow \infty} P_{m,n} = \Pi$ . It follows that the chain is strongly ergodic with  $\lim_{n \rightarrow \infty} P_{m,n} = \Pi$ ,  $\forall m \geq 0$ .  $\square$

A special case of the hypothesis of Theorem 1.18 is  $u_1 = u_2 = \dots := u \in K$ . Below we give a sufficient condition for  $(P_{s,t_l})_{\{u\}} > 0$ ,  $\forall l \geq 1$ . For this, we need the following notion.

**Definition 1.19** (see, e.g., [12, p. 80]). Let  $T \in N_{m,n}$ . We say that  $T$  is a *column-allowable matrix* if it has at least one positive entry in each column.

**THEOREM 1.20.** *Let  $(P_n)_{n \geq 1}$  be a Markov chain. Let  $\emptyset \neq K \subseteq S$  and  $s \geq 0$ . If  $\exists t > s, \exists u = u(t) \in K$  such that  $(P_{s,t})_{\{u\}} > 0$  and there exists a sequence  $t < t_1 < t_2 < \dots$  such that  $P_{t,t_l}$  is a column-allowable matrix,  $\forall l \geq 1$ , then  $(P_{s,t_l})_{\{u\}} > 0, \forall l \geq 1$ .*

*Proof.* Obvious.  $\square$

The following result is closely related to Theorem 2.1, (1) $\Leftrightarrow$ (3), in [6].

**THEOREM 1.21.** *Let  $(P_n)_{n \geq 1}$  be a Markov chain. Let  $\emptyset \neq K \subseteq S$  included in a strongly ergodic class on  $A \times B$  with respect to  $\Sigma$ . Then the following statements are equivalent.*

- (i) *The chain is strongly ergodic on  $A \times B$  with respect to  $\Sigma$ .*
- (ii) *The chain is weakly ergodic on  $A \times B$  with respect to  $\Sigma$ .*

*Proof.* Obvious.  $\square$

**THEOREM 1.22 ([3]).** *Let  $(P_n)_{n \geq 1}$  be a Markov chain. Then it is weakly ergodic if and only if there exists a strictly increasing sequence  $0 \leq n_1 < n_2 < \dots$  (of natural integers) such that  $\sum_{s \geq 1} \alpha(P_{n_s, n_{s+1}}) = \infty$ .*

*Proof.* See, e.g., [3] or [4, p. 219].  $\square$

**THEOREM 1.23 ([10]).** *Let*

$$P_n = \begin{pmatrix} Q_n & 0 \\ R_n & T_n \end{pmatrix}, \quad n \geq 1,$$

*be a Markov chain and  $(K_1, K_2) \in \text{Par}(S)$ , where  $(P_n)_{K_1}^{K_1} = Q_n, \forall n \geq 1$ . If*

- (i)  *$K_1$  is included in a weakly (respectively, strongly) ergodic class;*
- (ii)  *$T_n$  is lower triangular,  $\forall n \geq 1$ , or it is upper triangular,  $\forall n \geq 1$ ;*
- (iii)  *$\prod_{n \geq t} (P_n)_{ii} = 0, \forall t \geq 1, \forall i \in K_2$ ,*

*then  $(P_n)_{n \geq 1}$  is weakly (respectively, strongly) ergodic.*

*Proof.* See [10].  $\square$

## 2. RELIABILITY THEORY

In this section we consider the Markov chains from [5]. Generally speaking, the matrices corresponding to a reliability structure depend on the number of structure components and time (time in the sense of Markov chain theory); [1] studies especially the case where the matrices depend on both the number of structure components and time while [5] the case where these only depend on time. Here we do not set forth the Markov chain approach of reliability

structures (for this see [5]), but only we define and study the Markov chains (without their meaning) corresponding to reliability structures from [5].

The underlying Markov chain we need is  $(X_n)_{n \geq 0}$  with state space  $S = \{0, 1, \dots, r\}$ , initial distribution  $\pi_0$  with  $\text{supp } \pi_0 \subseteq \{0, 1, \dots, r-1\}$ , where  $\text{supp } \pi_0 := \{i \mid i \in S \text{ and } (\pi_0)_i > 0\}$  (*the support of  $\pi_0$* ), and transition matrices  $(P_n)_{n \geq 1}$  with  $P_n \in \mathcal{R}_{r+1}^r$  (the rows and columns of these matrices are labelled  $0, 1, \dots, r$ ),  $\forall n \geq 1$ . We call it *the reliability Markov chain* and frequently shall refer to it as the reliability (finite) Markov chain  $(P_n)_{n \geq 1}$ .

Further, we define reliability Markov chains corresponding to reliability structures from [5] (where they were considered without naming them). We divide them into three classes as follows.

*Class I.* This contains:

1. *Series Markov chains.* These are the Markov chains with state space  $S = \{0, 1\}$  ( $r = 1$ ), initial distribution  $\pi_0 = (1, 0)$ , and transition matrices

$$P_n = \begin{pmatrix} p_n & q_n \\ & 1 \end{pmatrix}, \quad n \geq 1$$

( $p_n + q_n = 1$  and we can omit 0,  $\forall n \geq 1$ ).

2. *k-out-of- $\infty$ : F Markov chains.* These are the Markov chains with state space  $S = \{0, 1, \dots, k\}$  ( $k \geq 1$ ), initial distribution  $\pi_0$  with  $\text{supp } \pi_0 \subseteq \{0, 1, \dots, k-1\}$ , and transition matrices

$$P_n = \begin{pmatrix} p_n & q_n & & & & \\ & p_n & q_n & & & \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ & & & & p_n & q_n \\ & & & & & 1 \end{pmatrix}, \quad n \geq 1.$$

We note that a series Markov chain is in fact a 1-out-of- $\infty$ : F Markov chain.

3. *Weighted k-out-of- $\infty$ : F Markov chains.* These are the Markov chains with state space  $S = \{0, 1, \dots, k\}$ , initial distribution  $\pi_0$  with  $\text{supp } \pi_0 \subseteq \{0, 1, \dots, k-1\}$ , and transition matrices

$$P_n = \begin{pmatrix} p_n & \dots & q_n & & & \\ & p_n & & q_n & & \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ & & & & p_n & q_n \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ & & & & p_n & q_n \\ & & & & & 1 \end{pmatrix}, \quad n \geq 1,$$

with  $(P_n)_{i,i+w_n} = q_n$ ,  $\forall n \geq 1$ ,  $\forall i \in S$ ,  $i + w_n \leq k$ , where  $w_n$  is a natural number,  $1 \leq w_n \leq k$ ,  $\forall n \geq 1$ . We call  $w_n$  the *weight* of  $P_n$ ,  $\forall n \geq 1$ .

We note that a  $k$ -out-of- $\infty$ :  $F$  Markov chain is in fact a weighted  $k$ -out-of- $\infty$ :  $F$  Markov chain with  $w_n = 1$ ,  $\forall n \geq 1$ .

*Class II.* This contains:

1. *Consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chains.* These are the Markov chains with state space  $S = \{0, 1, \dots, k\}$ , initial distribution  $\pi_0$  with  $\text{supp } \pi_0 \subseteq \{0, 1, \dots, k-1\}$ , and transition matrices

$$P_n = \begin{pmatrix} p_n & q_n & & & & \\ p_n & & q_n & & & \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ p_n & & & & q_n & \\ & & & & & 1 \end{pmatrix}, \quad n \geq 1.$$

2. *Weighted consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chains.* These are the Markov chains with state space  $S = \{0, 1, \dots, k\}$ , initial distribution  $\pi_0$  with  $\text{supp } \pi_0 \subseteq \{0, 1, \dots, k-1\}$ , and transition matrices

$$P_n = \begin{pmatrix} p_n & \cdots & q_n & & & \\ p_n & & & q_n & & \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ p_n & & & & & q_n \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ p_n & & & & & q_n \\ & & & & & 1 \end{pmatrix}, \quad n \geq 1,$$

with  $(P_n)_{i,i+w_n} = q_n$ ,  $\forall n \geq 1$ ,  $\forall i \in S$ ,  $i + w_n \leq k$ , where  $w_n$  is a natural number,  $1 \leq w_n \leq k$ ,  $\forall n \geq 1$ . We call  $w_n$  the *weight* of  $P_n$ ,  $\forall n \geq 1$ .

3.  *$m$ -consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chains.* These are the Markov chains with state space  $S = \{0, 1, \dots, mk\}$ , initial distribution  $\pi_0$  with  $\text{supp } \pi_0 \subseteq \{0, 1, \dots, mk-1\}$ , and transition matrices

$$P_n = \begin{pmatrix} V_n & Y_n & & & & \\ & V_n & Y_n & & & \\ \cdot & \cdot & \cdot & & & \\ & & & V_n & Y_n & \\ & & & & V_n & q_n e'_k(k) \\ & & & & & 1 \end{pmatrix}, \quad n \geq 1,$$

where

$$V_n = \begin{pmatrix} p_n & q_n & & & \\ p_n & & q_n & & \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_n & & & & q_n \\ p_n & & & & \end{pmatrix}, \quad Y_n = \begin{pmatrix} & & & & \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ & & & & \\ q_n & & & & \end{pmatrix}$$

are  $k \times k$  matrices,  $\forall n \geq 1$ .

Obviously, a consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain is both a weighted consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain with  $w_n = 1$ ,  $\forall n \geq 1$ , and a 1-consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain.

4. *Weighted  $m$ -consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chains.* These are the Markov chains with state space  $S = \{0, 1, \dots, mk\}$ , initial distribution  $\pi_0$  with  $\text{supp } \pi_0 \subseteq \{0, 1, \dots, mk - 1\}$ , and transition matrices

$$P_n = \begin{pmatrix} V_n & Y_n & & & \\ & V_n & Y_n & & \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ & & & V_n & Y_n \\ & & & V_n & q_n e'_k(k) \\ & & & & 1 \end{pmatrix}, \quad n \geq 1,$$

where

$$V_n = \begin{pmatrix} p_n & \cdots & q_n & & \\ p_n & & q_n & & \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_n & & & & q_n \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_n & & & & \end{pmatrix}, \quad Y_n = \begin{pmatrix} & & & & \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ & & & & \\ q_n & & & & \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ q_n & & & & \end{pmatrix}$$

are  $k \times k$  matrices with  $(V_n)_{i, i+w_n} = (Y_n)_{k-w_n+j, 0} = q_n$  (we label rows and columns of  $V_n$  and  $Y_n$  as  $0, 1, \dots, k-1$ ),  $\forall n \geq 1$ ,  $\forall i \in \{0, 1, \dots, k-1\}$ ,  $i+w_n \leq k-1$ ,  $\forall j \in \{0, 1, \dots, w_n-1\}$ , where  $w_n$  is a natural number,  $1 \leq w_n \leq k$ ,  $\forall n \geq 1$ . We call  $w_n$  the weight of  $P_n$ ,  $\forall n \geq 1$ . Note that this subclass of Markov chains does not exist in [5]. Also, note that an  $m$ -consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain is a weighted  $m$ -consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain with  $w_n = 1$ ,  $\forall n \geq 1$ .

*Class III.* This contains  $u$ -within-consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chains. For ease of the illustration (following [5]) for  $u = 2$  these are the Markov chains with state space  $S = \{0, 1, \dots, k+1\}$ , initial distribution  $\pi_0$

with  $\text{supp } \pi_0 \subseteq \{0, 1, \dots, k\}$ , and transition matrices

$$P_n = \begin{pmatrix} p_n & q_n & & & & & \\ & & p_n & & & & q_n \\ & & & p_n & & & q_n \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ & & & & p_n & q_n \\ p_n & q_n & & & & 0 \\ 0 & 0 & & & & 1 \end{pmatrix}, \quad n \geq 1.$$

Note that in this paper the above case is only considered.

Let  $(P_n)_{n \geq 1}$  be a reliability Markov chain. Let  $f(r+1) = e(r+1) - e_{r+1}(r+1) \in \mathbf{R}^{r+1}$  (for  $e(r+1)$  and  $e_{r+1}(r+1)$  see Section 1). Following [5, Theorem 3.1] the reliability  $R_v$  and unreliability  $F_v$  of a  $v$ -component system linearly arranged and labelled  $1, 2, \dots, v$  and which correspond, in the Markovian approach, to initial the distribution  $\pi_0$  and matrices  $P_1, P_2, \dots, P_v$  are given by

$$R_v = \pi_0 P_{0,v} f'(r+1) \quad \text{and} \quad F_v = \pi_0 P_{0,v} e'_{r+1}(r+1), \quad \text{respectively, } \forall v \geq 1.$$

Setting  $R_0 = 1$  and  $F_0 = 0$  we can call  $R_v$  and  $F_v$  the reliability and the unreliability at time  $v$  ( $v \geq 0$ ) of reliability Markov chain  $(P_n)_{n \geq 1}$ , respectively. Obviously,

$$F_v = 1 - R_v, \quad \forall v \geq 0.$$

**THEOREM 2.1.** *Let  $(P_n)_{n \geq 1}$  be a reliability Markov chain. Then*

$$R_v = \sum_{i \in \text{supp } \pi_0} (\pi_0)_i \sum_{j=0}^{r-1} (P_{0,v})_{ij} \quad \text{and} \quad F_v = \sum_{i \in \text{supp } \pi_0} (\pi_0)_i (P_{0,v})_{ir}, \quad \forall v \geq 1.$$

*In particular, if  $\pi_0 = (1, 0, \dots, 0)$  (this is the usual case in the reliability theory), then*

$$R_v = \sum_{j=0}^{r-1} (P_{0,v})_{0,j} \quad \text{and} \quad F_v = (P_{0,v})_{0,r}, \quad \forall v \geq 1.$$

*Proof.* Obvious.  $\square$

**THEOREM 2.2.** *Let  $(P_n)_{n \geq 1}$  be a reliability Markov chain. Then*

$$\exists \lim_{v \rightarrow \infty} R_v, \quad \lim_{v \rightarrow \infty} F_v.$$

*Proof.* This follows from Theorems 1.15(i) and 2.1.  $\square$

Set

$$R_\infty = \lim_{v \rightarrow \infty} R_v \quad \text{and} \quad F_\infty = \lim_{v \rightarrow \infty} F_v.$$

We call  $R_\infty$  and  $F_\infty$  *the limit reliability* and *the limit unreliability*, respectively.

Further, we give necessary and/or sufficient conditions for  $R_\infty = 0$  (equivalently, for  $F_\infty = 1$ ). The following result gives necessary and sufficient conditions for  $R_\infty = 0$ .

**THEOREM 2.3.** *Let  $(P_n)_{n \geq 1}$  be a reliability Markov chain. Let  $\Sigma_1 = (\{i\})_{i \in S}$  and  $\Sigma_2 = (\{0, 1, \dots, r-1\}, \{r\})$ . Then the following statements are equivalent.*

- (i)  $R_\infty = 0$ .
- (ii)  $\text{supp } \pi_0 \cup \{r\}$  is included in a weakly ergodic class at time 0 with respect to  $\Sigma_1$ .
- (iii)  $\text{supp } \pi_0 \cup \{r\}$  is included in a strongly ergodic class at time 0 with respect to  $\Sigma_1$ .
- (iv)  $\text{supp } \pi_0 \cup \{r\}$  is included in a weakly ergodic class at time 0 with respect to  $\Sigma_2$ .
- (v)  $\text{supp } \pi_0 \cup \{r\}$  is included in a strongly ergodic class at time 0 with respect to  $\Sigma_2$ .

*Proof.* (i)  $\Leftrightarrow$  (iii) See Theorem 2.1.

(ii)  $\Rightarrow$  (iii) Obvious, since  $\{r\}$  is included in a strongly ergodic class with respect to  $\Sigma_1$ .

(iii)  $\Rightarrow$  (ii) Obvious.

(iv)  $\Rightarrow$  (v) Obvious, since  $\{r\}$  is included in a strongly ergodic class with respect to  $\Sigma_2$ .

(v)  $\Rightarrow$  (iv) Obvious.

(ii)  $\Leftrightarrow$  (iv) Obvious.  $\square$

**THEOREM 2.4.** *Let  $(P_n)_{n \geq 1}$  be a reliability Markov chain. Let  $\Sigma_1 = (\{i\})_{i \in S}$  and  $\Sigma_2 = (\{0, 1, \dots, r-1\}, \{r\})$ . Then the following statements are equivalent.*

- (i) The chain is weakly ergodic on (time set)  $B$  with respect to  $\Sigma_1$ .
- (ii) The chain is strongly ergodic on  $B$  with respect to  $\Sigma_1$ .
- (iii) The chain is weakly ergodic on  $B$  with respect to  $\Sigma_2$ .
- (iv) The chain is strongly ergodic on  $B$  with respect to  $\Sigma_2$ .

*Proof.* (i)  $\Leftrightarrow$  (ii) See Theorem 1.21.

(i)  $\Leftrightarrow$  (iii) Obvious.

(iii)  $\Leftrightarrow$  (iv) See Theorem 1.21.  $\square$

The following result gives a sufficient condition for  $R_\infty = 0$ . (For other sufficient conditions, see Theorem 2.3.)

**THEOREM 2.5.** *Let  $(P_n)_{n \geq 1}$  be a reliability Markov chain. Let  $\emptyset \neq B \subseteq \mathbf{N}$  with  $0 \in B$  and  $\Sigma = (\{i\})_{i \in S}$ . If the chain is weakly ergodic on  $B$  with respect to  $\Sigma$ , then  $R_\infty = 0$ .*

*Proof.* Obvious.  $\square$

A problem is the use of Theorems 1.17 and 1.18. We note that in any reliability Markov chain  $(P_n)_{n \geq 1}$  the set  $\{r\}$  is included in a strongly ergodic class at time 0.

**THEOREM 2.6.** *Let  $(P_n)_{n \geq 1}$  be a  $k$ -out-of- $\infty$ :  $F$ , or consecutive- $k$ -out-of- $\infty$ :  $F$ , or 2-within-consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain (with initial distribution  $\pi_0$  (the case  $\pi_0 = (1, 0, \dots, 0)$  is closely related to the conclusions below)).*

- (i) *If  $p_1, q_1, p_2, q_2, \dots, p_k, q_k > 0$ , then  $(P_{0,k})_{\{0\}} > 0$ .*
- (ii) *If  $p_l, q_l > 0$ ,  $\forall l \geq 1$ , then  $(P_{0,n})_{\{0\}} > 0$ ,  $\forall n \geq k$ .*
- (iii) *If  $(P_n)_{n \geq 1}$  is a  $k$ -out-of- $\infty$ :  $F$  Markov chain,  $p_l > 0$ ,  $\forall l \geq 1$ , and there exists a strictly increasing sequence  $1 \leq l_1 < l_2 < \dots$  (of natural integers) with  $q_{l_h} > 0$ ,  $\forall h \geq 1$ , then  $\exists n_0 \geq k$  such that  $(P_{0,n})_{\{0\}} > 0$ ,  $\forall n \geq n_0$ .*

*Proof.* (i) Obvious (by induction).

(ii) We have

$$(P_{0,n})_{\{0\}} = (P_{0,k})_{\{0\}} P_{k,n} > 0, \quad \forall n > k,$$

because  $(P_{0,k})_{\{0\}} > 0$  and  $P_{k,n}$  is a column-allowable matrix,  $\forall n > k$ .

(iii) We have  $P_l = I_{k+1}$ , if  $q_l = 0$ . Now, cf. (i) and (ii).  $\square$

*Remark 2.7.* In general, we have no results similar to Theorem 2.6 for weighted Markov chains. We give an example for weighted  $k$ -out-of- $\infty$ :  $F$  Markov chains. Let  $k = 3$  and  $w_n = 2$ ,  $\forall n \geq 1$ . Then

$$P_n = \begin{pmatrix} p_n & 0 & q_n & 0 \\ 0 & p_n & 0 & q_n \\ 0 & 0 & p_n & q_n \\ 0 & 0 & 0 & 1 \end{pmatrix}, \quad \forall n \geq 1.$$

Obviously,  $(P_{m,n})_{0,1} = 0$ ,  $\forall m, n, 0 \leq m < n$ ,  $\forall l \geq 1$ ,  $\forall p_l, q_l \in [0, 1]$ .

**THEOREM 2.8.** *Let  $(P_n)_{n \geq 1}$  be an  $m$ -consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain (with initial distribution  $\pi_0$  (the case  $\pi_0 = (1, 0, \dots, 0)$  is closely related to the conclusions below)).*

- (i) *If  $p_1, q_1, p_2, q_2, \dots, p_{mk}, q_{mk} > 0$ , then  $(P_{0,mk})_{\{0\}} > 0$ .*
- (ii) *If  $p_l, q_l > 0$ ,  $\forall l \geq 1$ , then  $(P_{0,n})_{\{0\}} > 0$ ,  $\forall n \geq mk$ .*

*Proof.* (i) Obvious (by induction;  $P_n$  has  $(P_n)_{0,1} = (P_n)_{1,2} = \dots = (P_n)_{mk-1,mk} = q_n$ ,  $\forall n \geq 1$ ).

(ii) This is similar to the proof of Theorem 2.6(ii).  $\square$



Further, we give necessary and/or sufficient conditions for strong ergodicity (equivalently, cf. Theorem 2.4, for weak ergodicity) (also, remember that in this case  $A = S$ ,  $B = \mathbf{N}$ , and  $\Sigma = (\{i\})_{i \in S}$  (see Section 1)).

**THEOREM 2.9.** *Let  $(P_n)_{n \geq 1}$  be a reliability Markov chain belonging to the union of Classes I, II, and III. If  $\exists a > 0$  such that  $p_n, q_n > a$ ,  $\forall n \geq 1$ , then the chain is strongly ergodic.*

*Proof.* If  $(P_n)_{n \geq 1}$  is a  $k$ -out-of- $\infty$ :  $F$  Markov chain, then

$$P_n = \begin{pmatrix} p_n & q_n & & & & \\ & p_n & q_n & & & \\ & \cdot & \cdot & \cdot & \cdot & \cdot \\ & & & & p_n & q_n \\ & & & & & 1 \end{pmatrix} \geq \begin{pmatrix} a & a & & & & \\ & a & a & & & \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ & & & & a & a \\ & & & & & 1 \end{pmatrix} := P, \quad \forall n \geq 1.$$

Now, we can use Theorem 1.11 for  $P$  even if  $P \in N_{k+1}$ . It follows that  $\alpha(P^k) := b > 0$ . This implies  $\alpha(P_{m,m+k}) \geq b$ ,  $\forall m \geq 0$ . Now, by Theorem 1.22, the chain  $(P_n)_{n \geq 1}$  is weakly ergodic. Strong ergodicity now follows from Theorem 2.4.

The others cases have similar proofs.  $\square$

**THEOREM 2.10.** *Let  $(P_n)_{n \geq 1}$  be a reliability Markov chain belonging to the union of Classes I, II, and III.*

(i) *If  $\sum_{n \geq 1} p_n < \infty$ , then  $(P_n)_{n \geq 1}$  is strongly ergodic.*

(ii) *If  $(P_n)_{n \geq 1}$  is strongly ergodic, then  $\sum_{n \geq 1} q_n = \infty$ .*

*Proof.* (i) Let  $(P'_n)_{n \geq 1}$  be a perturbation of the first type of  $(P_n)_{n \geq 1}$ , where

$$(P'_n)_{ij} = \begin{cases} 0 & \text{if } q_n \text{ is not assigned to entry } (i, j) \text{ of } P_n, \\ 1 & \text{if } q_n \text{ is assigned to entry } (i, j) \text{ of } P_n, \end{cases}$$

$\forall n \geq 1$ ,  $\forall i, j \in S$  ( $S$  is state space of  $(P_n)_{n \geq 1}$  and  $(P'_n)_{n \geq 1}$ ).

*Case 1.*  $(P_n)_{n \geq 1}$  belongs to the union of Classes I and II. It follows from Theorem 1.23 that  $(P'_n)_{n \geq 1}$  is strongly ergodic. Now, by Theorem 1.10,  $(P_n)_{n \geq 1}$  is strongly ergodic.

*Case 2.*  $(P_n)_{n \geq 1}$  belongs to Class III (only the case  $u = 2$ ). First, it follows that  $(P'_n)_{n \geq 1}$  is weakly ergodic, because

$$P'_n P'_{n+1} = \begin{pmatrix} 0 & 0 & \cdots & 1 \\ 0 & 0 & \cdots & 1 \\ \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdots & 1 \end{pmatrix}, \quad \forall n \geq 1.$$

Second, by Theorem 1.10,  $(P_n)_{n \geq 1}$  is weakly ergodic. Third, by Theorem 1.21,  $(P_n)_{n \geq 1}$  is strongly ergodic.

(ii) For  $(P_n)_{n \geq 1}$  belonging to Class I, see Theorem 2.11 below. Further, for any  $(P_n)_{n \geq 1}$  belonging to the union of Classes II and III, the proof is similar to “ $\Rightarrow$ ” from the proof of Theorem 2.11 below.  $\square$

**THEOREM 2.11.** *Let  $(P_n)_{n \geq 1}$  be a weighted  $k$ -out-of- $\infty$ :  $F$  Markov chain. Then the chain is strongly ergodic if and only if*

$$\sum_{n \geq 1} q_n = \infty.$$

*Proof.* “ $\Rightarrow$ ” Suppose that  $\sum_{n \geq 1} q_n < \infty$ . Then the chain  $(P'_n)_{n \geq 1}$ , where  $P'_n = I_{k+1}$ ,  $\forall n \geq 1$ , is a perturbation of the first type of  $(P_n)_{n \geq 1}$ . Because  $(P'_n)_{n \geq 1}$  is strongly  $(\{i\})_{i \in S}$ -ergodic, it follows from Theorem 1.10 that  $(P_n)_{n \geq 1}$  is strongly  $\Delta$ -ergodic with  $\Delta \neq (S)$  (moreover, using Theorem 1.45 in [9], we have  $\Delta = (\{i\})_{i \in S}$ ), and we reached a contradiction.

“ $\Leftarrow$ ” See Theorem 1.23.  $\square$

**Remark 2.12.** If  $(P_n)_{n \geq 1}$  is a consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain, then condition  $\sum_{n \geq 1} q_n = \infty$  is not sufficient for strong ergodicity. Indeed, for  $k \geq 2$ , let

$$P_{2n-1} = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ 1 & 0 & 0 & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 1 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix} := E, \quad P_{2n} = \begin{pmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & \cdots & 1 \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix} := F, \quad \forall n \geq 1.$$

(A generalization:  $P_n \in \{E, F\}$ ,  $\forall n \geq 1$ ,  $E$  appears a least once in any  $l$  consecutive matrices belonging to  $(P_n)_{n \geq 1}$ , where  $2 \leq l \leq k$  ( $k \geq 2$ ), and there exists a sequence  $1 \leq n_1 < n_2 < \cdots$  such that  $P_{n_i} = F$ ,  $\forall i \geq 1$ .) We have  $\sum_{n \geq 1} q_n = \infty$  and

$$EF = \begin{pmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}, \quad EFE = E.$$

Therefore, the chain  $(P_n)_{n \geq 1}$  is not strongly ergodic.

THEOREM 2.13. Let  $(P_n)_{n \geq 1}$  be a consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain. Then

$$\alpha(P_{m,m+k}) = \mu(P_{m,m+k}) = \mu((P_{m,m+k})^{\{k\}}) = q_{m+1}q_{m+2} \cdots q_{m+k}, \quad \forall m \geq 0.$$

*Proof.* The equalities  $\alpha(P_{m,m+k}) = \mu(P_{m,m+k}) = \mu((P_{m,m+k})^{\{k\}})$  follow from Theorem 1.13. Further, let us prove that

$$\mu((P_{m,m+k})^{\{k\}}) = q_{m+1}q_{m+2} \cdots q_{m+k}, \quad \forall m \geq 0.$$

We have

$$\begin{aligned} P_n &= \begin{pmatrix} p_n & q_n & 0 & \cdots & 0 \\ p_n & 0 & q_n & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_n & 0 & 0 & \cdots & q_n \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix} = \\ &= \begin{pmatrix} p_n & 0 & 0 & \cdots & 0 \\ p_n & 0 & 0 & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_n & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \end{pmatrix} + \begin{pmatrix} 0 & q_n & 0 & \cdots & 0 \\ 0 & 0 & q_n & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & \cdots & q_n \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}, \quad \forall n \geq 1. \end{aligned}$$

Setting

$$G_n = \begin{pmatrix} p_n & 0 & 0 & \cdots & 0 \\ p_n & 0 & 0 & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ p_n & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \end{pmatrix}, \quad H_n = \begin{pmatrix} 0 & q_n & 0 & \cdots & 0 \\ 0 & 0 & q_n & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & \cdots & q_n \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}, \quad \forall n \geq 1,$$

we have

$$P_n = G_n + H_n, \quad \forall n \geq 1.$$

First, we prove that

$$(H_{m,m+t})_{0,k} = 0, \quad \forall m \geq 0, \quad \forall t, \quad 1 \leq t \leq k-1.$$

Indeed,

$$\begin{aligned} &(H_{m,m+t})_{0,k} = \\ &= (H_{m+1})_{0,1} (H_{m+2})_{1,2} \cdots (H_{m+t})_{t-1,k} = 0, \quad \forall m \geq 0, \quad \forall t, \quad 1 \leq t \leq k-1. \end{aligned}$$

Second, we prove that

$$(P_{m+k-v,m+k})^{\{k\}} = (H_{m+k-v,m+k})^{\{k\}}, \quad \forall m \geq 0, \quad \forall v, \quad 1 \leq v \leq k.$$

Indeed, this follows by induction with respect to  $v$ .

*Step 1.*  $v = 1$ . We have

$$(P_{m+k-1,m+k})^{\{k\}} = (P_{m+k})^{\{k\}} = (G_{m+k} + H_{m+k})^{\{k\}} =$$

$$= (G_{m+k})^{\{k\}} + (H_{m+k})^{\{k\}} = (H_{m+k})^{\{k\}} = (H_{m+k-1,m+k})^{\{k\}}, \quad \forall m \geq 0.$$

Step 2.  $v \mapsto v+1$  ( $1 \leq v+1 \leq k$ ). We have

$$\begin{aligned} (P_{m+k-v-1,m+k})^{\{k\}} &= P_{m+k-v} (P_{m+k-v,m+k})^{\{k\}} = \\ &= (G_{m+k-v} + H_{m+k-v}) (H_{m+k-v,m+k})^{\{k\}} = \\ (G_{m+k-v} (H_{m+k-v,m+k})^{\{k\}} &= 0 \text{ since } (H_{m+k-v,m+k})_{0,k} = 0, \forall m \geq 0) \\ &= H_{m+k-v} (H_{m+k-v,m+k})^{\{k\}} = (H_{m+k-v} H_{m+k-v,m+k})^{\{k\}} = \\ &= (H_{m+k-v-1,m+k})^{\{k\}}, \quad \forall m \geq 0. \end{aligned}$$

Third, we show that

$$(H_{m,m+k})^{\{k\}} = \begin{pmatrix} q_{m+1} \cdots q_{m+k} \\ q_{m+1} \cdots q_{m+k-1} \\ \vdots \\ q_{m+1} \\ 1 \end{pmatrix}, \quad \forall m \geq 0.$$

For this, setting

$$Z_n = \begin{pmatrix} 0 & q_n & 0 & \cdots & 0 \\ 0 & 0 & q_n & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & \cdots & q_n \\ 0 & 0 & 0 & \cdots & 0 \end{pmatrix}, \quad \forall n \geq 1,$$

and

$$Z = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix},$$

we have  $H_n = Z_n + Z$ ,  $\forall n \geq 1$ . Further, because

$$ZZ_n = 0, \quad Z_n Z = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & \cdots & q_n \\ 0 & 0 & 0 & \cdots & 0 \end{pmatrix}, \quad \forall n \geq 1, \text{ and } ZZ = Z,$$

we have

$$\begin{aligned} H_{m,m+k} &= H_{m+1} H_{m+2} \cdots H_{m+k} = (Z_{m+1} + Z)(Z_{m+2} + Z) \cdots (Z_{m+k} + Z) = \\ &= Z_{m+1} [(Z_{m+2} + Z) \cdots (Z_{m+k} + Z)] + Z [(Z_{m+2} + Z) \cdots (Z_{m+k} + Z)] = \\ &= Z_{m+1} [(Z_{m+2} + Z) \cdots (Z_{m+k} + Z)] + Z = \end{aligned}$$

$$\begin{aligned}
&= Z_{m+1} \{ Z_{m+2} [(Z_{m+3} + Z) \cdots (Z_{m+k} + Z)] + Z [(Z_{m+3} + Z) \cdots (Z_{m+k} + Z)] \} + \\
&\quad + Z = Z_{m+1} Z_{m+2} [(Z_{m+3} + Z) \cdots (Z_{m+k} + Z)] + Z_{m+1} Z + Z = \\
&\text{(by induction)} \\
&= Z_{m+1} Z_{m+2} \cdots Z_{m+k} + Z_{m+1} Z_{m+2} \cdots Z_{m+k-1} Z + \cdots + Z_{m+1} Z + Z = \\
&= \begin{pmatrix} 0 & \cdots & 0 & q_{m+1} q_{m+2} \cdots q_{m+k} \\ 0 & \cdots & 0 & 0 \\ \cdot & \cdot & \cdot & \cdot \\ 0 & \cdots & 0 & 0 \end{pmatrix} + \\
&\quad + \begin{pmatrix} 0 & \cdots & 0 & 0 \\ 0 & \cdots & 0 & q_{m+1} q_{m+2} \cdots q_{m+k-1} \\ \cdot & \cdot & \cdot & \cdot \\ 0 & \cdots & 0 & 0 \end{pmatrix} + \\
&\quad + \cdots + \begin{pmatrix} 0 & \cdots & 0 & 0 \\ \cdot & \cdot & \cdot & \cdot \\ 0 & \cdots & 0 & q_{m+1} \\ 0 & \cdots & 0 & 0 \end{pmatrix} + \begin{pmatrix} 0 & \cdots & 0 & 0 \\ \cdot & \cdot & \cdot & \cdot \\ 0 & \cdots & 0 & 0 \\ 0 & \cdots & 0 & 1 \end{pmatrix} = \\
&= \begin{pmatrix} 0 & \cdots & 0 & q_{m+1} q_{m+2} \cdots q_{m+k} \\ 0 & \cdots & 0 & q_{m+1} q_{m+2} \cdots q_{m+k-1} \\ \cdot & \cdot & \cdot & \cdot \\ 0 & \cdots & 0 & q_{m+1} \\ 0 & \cdots & 0 & 1 \end{pmatrix}, \quad \forall m \geq 0.
\end{aligned}$$

Consequently,

$$(H_{m,m+k})^{\{k\}} = \begin{pmatrix} q_{m+1} q_{m+2} \cdots q_{m+k} \\ q_{m+1} q_{m+2} \cdots q_{m+k-1} \\ \vdots \\ q_{m+1} \\ 1 \end{pmatrix}, \quad \forall m \geq 0.$$

Hence

$$\mu((P_{m,m+k})^{\{k\}}) = \mu((H_{m,m+k})^{\{k\}}) = q_{m+1} q_{m+2} \cdots q_{m+k}, \quad \forall m \geq 0. \quad \square$$

**THEOREM 2.14.** *Let  $(P_n)_{n \geq 1}$  be a consecutive- $k$ -out-of- $\infty$ :  $F$  Markov chain.*

(i) If  $(P_n)_{n \geq 1}$  is strongly ergodic, then  $\forall l, \left[\frac{k-2}{2}\right] < l < k$ , we have

$$\sum_{s \geq 0} \min(q_{s(k-l)+1}, q_{s(k-l)+2}, \dots, q_{s(k-l)+k-l}) = \infty.$$

(ii) If  $\exists t, 0 \leq t \leq k-1$ , such that

$$\sum_{s \geq 0} q_{sk+t+1} q_{sk+t+2} \cdots q_{sk+t+k} = \infty,$$

then  $(P_n)_{n \geq 1}$  is strongly ergodic.

*Proof.* (i) Let  $\left[\frac{k-2}{2}\right] < l < k$ . Suppose that

$$\sum_{s \geq 0} \min(q_{s(k-l)+1}, q_{s(k-l)+2}, \dots, q_{s(k-l)+k-l}) < \infty.$$

Let  $n_0 < n_1 < n_2 < \dots$ , where  $n_s$  is a natural integer such that

$$\min(q_{s(k-l)+1}, q_{s(k-l)+2}, \dots, q_{s(k-l)+k-l}) = q_{n_s}, \quad \forall s \geq 0.$$

(Therefore,  $n_s \in \{s(k-l)+1, s(k-l)+2, \dots, s(k-l)+k-l\}$ ,  $\forall s \geq 0$ .)

Let

$$P'_n = \begin{cases} P_n & \text{if } n \notin \{n_0, n_1, n_2, \dots\}, \\ Q & \text{if } n \in \{n_0, n_1, n_2, \dots\}, \end{cases}$$

where

$$Q = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdot \\ 1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 1 \end{pmatrix}.$$

We have  $\sum_{n \geq 1} \|P_n - P'_n\|_\infty < \infty$ . Because

$$n_{s+1} - n_s \leq (s+1)(k-l) + k-l - s(k-l) - 1 = 2(k-l) - 1 < k+1, \quad \forall s \geq 0,$$

we have

$$n_{s+1} - 1 - n_s < k, \quad \forall s \geq 0.$$

Consequently, the sequence  $(P'_n)_{n \geq 1}$  contains at most  $k-1$  consecutive matrices belonging to  $(P_n)_{n \geq 1}$ . Further,  $\forall m \geq 0, \forall u, v, 1 \leq u \leq k-1, 2 \leq v \leq k$ , we have

$$\begin{aligned} (P_{m,m+u}Q)_{\{0\}} &= (P_{m,m+u})_{\{0\}} Q = (1, 0, \dots, 0), \\ (P_{m,m+u}Q P_{m+u+1,m+u+v})_{\{0\}} &= (P_{m,m+u}Q)_{\{0\}} P_{m+u+1,m+u+v} = \\ &= (1, 0, \dots, 0) P_{m+u+1,m+u+v} = (P_{m+u+1,m+u+v})_{\{0\}}, \\ (P_{m,m+u}Q P_{m+u+1,m+u+v}Q)_{\{0\}} &= (P_{m,m+u}Q P_{m+u+1,m+u+v})_{\{0\}} Q = \\ &= (P_{m+u+1,m+u+v})_{\{0\}} Q = (1, 0, \dots, 0) \end{aligned}$$

etc. and

$$\begin{aligned}
 (P_{m,m+u}Q)_{\{k\}} &= (P_{m,m+u})_{\{k\}} Q = (0, 0, \dots, 1), \\
 (P_{m,m+u}QP_{m+u+1,m+u+v})_{\{k\}} &= (P_{m,m+u}Q)_{\{k\}} P_{m+u+1,m+u+v} = \\
 &= (0, 0, \dots, 1) P_{m+u+1,m+u+v} = (P_{m+u+1,m+u+v})_{\{k\}}, \\
 (P_{m,m+u}QP_{m+u+1,m+u+v}Q)_{\{k\}} &= (P_{m,m+u}QP_{m+u+1,m+u+v})_{\{k\}} Q = \\
 &= (P_{m+u+1,m+u+v})_{\{k\}} Q = (0, 0, \dots, 1)
 \end{aligned}$$

etc. It follows that  $(P'_n)_{n \geq 1}$  is not strongly ergodic. By Theorem 1.10,  $(P_n)_{n \geq 1}$  is not strongly ergodic, and we reached a contradiction.

(ii) See Theorems 1.21, 1.22, and 2.13.  $\square$

#### REFERENCES

- [1] M.T. Chao and J.C. Fu, *The reliability of a large series system under Markov structure*. Adv. in Appl. Probab. **23** (1991), 894–908.
- [2] R.L. Dobrushin, *Central limit theorem for nonstationary Markov chains*, I, II. Theory Probab. Appl. **1** (1956), 65–80, 329–383.
- [3] J. Hajnal, *Weak ergodicity in non-homogeneous Markov chains*. Proc. Cambridge Philos. Soc. **54** (1958), 233–246.
- [4] M. Iosifescu, *Finite Markov Processes and Their Applications*. Wiley, Chichester & Ed. Tehnică, Bucharest, 1980; corrected republication by Dover, Mineola, N.Y., 2007.
- [5] M.V. Koutras, *On a Markov chain approach for the study of reliability structures*. J. Appl. Probab. **33** (1996), 357–367.
- [6] U. Păun, *Ergodic theorems for finite Markov chains*. Math. Rep. (Bucur.) **3(53)** (2001), 383–390.
- [7] U. Păun, *New classes of ergodicity coefficients, and applications*. Math. Rep. (Bucur.) **6(56)** (2004), 141–158.
- [8] U. Păun, *General  $\Delta$ -ergodic theory of finite Markov chains*. Math. Rep. (Bucur.) **8(58)** (2006), 83–117.
- [9] U. Păun, *Perturbed finite Markov chains*. Math. Rep. (Bucur.) **9(59)** (2007), 183–210.
- [10] U. Păun,  *$\Delta$ -ergodic theory and simulated annealing*. Math. Rep. (Bucur.) **9(59)** (2007), 279–303.
- [11] U. Păun, *General  $\Delta$ -ergodic theory: an extension*. Rev. Roumaine Math. Pures Appl. **53** (2008), no. 2.
- [12] E. Seneta, *Non-negative Matrices and Markov Chains*, 2nd Edition. Springer-Verlag, Berlin–Heidelberg–New York, 1981. (Revised printing, 2006)

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